

Detecting membrane fouling occurrences in a full-scale membrane bioreactor with principal component analysis

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Abstract: The technique of principal component analysis (PCA) has been applied on high-frequency transmembrane pressure (TMP) data from a full-scale membrane bioreactor (MBR) for wastewater treatment, with the focus on membrane fouling occurrences. Additionally, logbook, inflow, temperature and permeability data were used to hypothesise the underlying causes for membrane fouling. PCA analysis was able to separate irreversible and reversible fouling events and thus describe the actual state of the membrane, while the additional data revealed the importance of dilution and temperature in relation to deteriorating sludge filterability and increasing filtration resistance.

Keywords: Membrane fouling; Full-scale membrane bioreactor; Principal components analysis

Introduction

Membrane fouling is an undesired mechanism in full-scale membrane bioreactor (MBR) plants for wastewater treatment. As advised by membrane producers, a fixed, experience-derived operational scheme is usually implemented including membrane aeration, backwash and chemical cleaning in conjunction with routine analyses on membrane permeability to safeguard operation. However, such fixed schemes are never optimal, ignore the dynamic nature of fouling and lack the flexibility to cope with changing influent, biological and membrane conditions. Moreover, they are usually very conservative. The resulting waste of energy, permeate, chemicals and membrane life-time provides significant potential for improving cost-efficiency based on dynamic and online control (Busch and Marquardt, 2009; Drews, 2010).

Principal component analysis (PCA) is an elegant technique to detect evolutions and trends in filtration performance of membranes through aforementioned data. Maere et al. (2012) demonstrated this for lab-scale TMP data and described its potential to monitor the membrane state and control the fouling process. In the current contribution, we extend this for the first time to a full-scale MBR historical data set.

Material and methods

At the full-scale sidestream MBR "De drie Ambachten" (Terneuzen, The Netherlands), TMP measurements were collected at a frequency of 1 per second for the period August 2011 - March 2012, in addition to detailed operational logbook data and daily average

values for permeability, aeration, temperature and flux. This vast amount of high frequency TMP measurements was reduced into 3 parameters for each membrane filtration cycle. These parameters, i.e. filtration pressure peak, backwash pressure peak and the slope of TMP increase during a filtration event, were chosen based on expert knowledge as in Maere et al. (2012) (Fig. 1.1). In contrast to latter study, the TMP profiles in this study, however, do not follow first order kinetics following the start of a filtration cycle. Therefore, the two first order parameters a and b describing the pressure build-up after backwash were omitted for further analysis.

Results and discussion

The evolution of the three selected parameters ($+\Delta P$, $-\Delta P$, S) based on TMP measurements for each filtration cycle ($t=455s$) is given in Fig. 1.2 and showing significant variation over time. The parameters were smoothed using a cubic spline filter to dampen the effect of outliers on the PCA analysis. Principal components (PCs) 1, 2 and 3 contained respectively 79.75, 18.13 and 2.12 % of the total variance. Retaining the first two components reduces the information of 455 data points per cycle into just 2 parameters visualised in a biplot for PC1 vs. PC2 (Fig. 1.3). Contrary to lab-scale data (Maere et al., 2012), the parameter estimation for full-scale PCA parameters requires a more elaborate approach. Current ideas include using recorded data about specific events and operational decisions, e.g. double backwash and more frequent chemical cleaning, as additional data sources and fine-tuning the model used to describe the TMP profiles to the specific plant. Once the appropriate parameter estimation is defined, a real-time algorithm can detect fouling patterns based on the actual membrane state.

The peak filtration pressure ($+\Delta P$) variance can be attributed to both reversible and irreversible fouling, whereas the peak backwash pressure ($-\Delta P$) variance indicates fouling that cannot be removed by a (chemical) enhanced backwash. $+\Delta P$ and the slope (S) are not correlated with $-\Delta P$, allowing to determine the nature of the fouling from the PC1 vs. PC2 scores in Fig. 1.4. Increasing PC1 scores indicate higher fouling propensity and vice versa. Decreasing PC2 scores indicate increased irreversible fouling and vice versa. Clear variations of both PC1&2 over time can be observed. Furthermore, the behaviour of PC1 vs. PC2 was further analysed based on daily average values for permeability and temperature (not shown) and additional information available in the logbook.

As an indicator of both reversible and irreversible fouling, PC1 showed most variation during November 2011 and January 2012. This behaviour coincided with periods of reduced permeability and heavy rainfall after relatively dry periods. In between, chemically enhanced backwashes (CEBs) obviously reduced $+\Delta P$ and thus PC1 decreased to less extreme values. Contrarily, PC2, as indicator of irreversible fouling, was almost not influenced by CEBs, which is quite surprising as this would be the intent of this action. Its behaviour closely followed temperature dynamics, i.e. decrease during wintertime and increase in springtime. Thus the behaviour of PC2 indicated an improvement of the membrane state, while the behaviour of PC1 indicated deteriorated sludge filterability.

In summary, PCA analysis was found to be a useful technique to detect reversible and irreversible membrane fouling patterns in vast amounts of full-scale TMP data. Further improvement of the analysis is required, but these preliminary results show the of the technique for full-scale operation, confirming earlier findings at lab scale. This opens new perspectives for monitoring, diagnosis and control of membrane fouling merely based on TMP data.

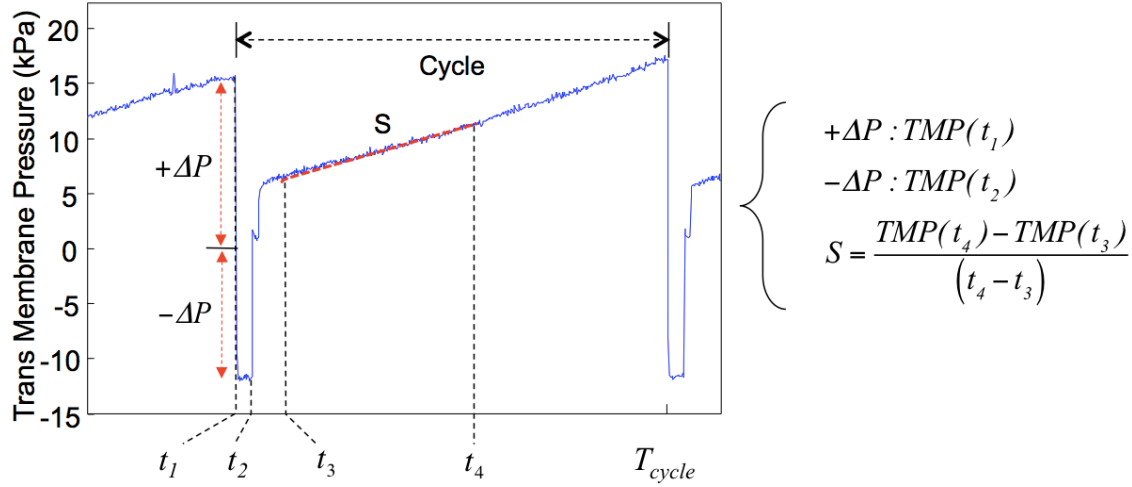


Figure 1.1: Expert-driven FPCA cycle parameters for a typical filtration cycle beginning at t_1 when the pressure is reversed to backwash. Adapted from Maere et al. (2012).

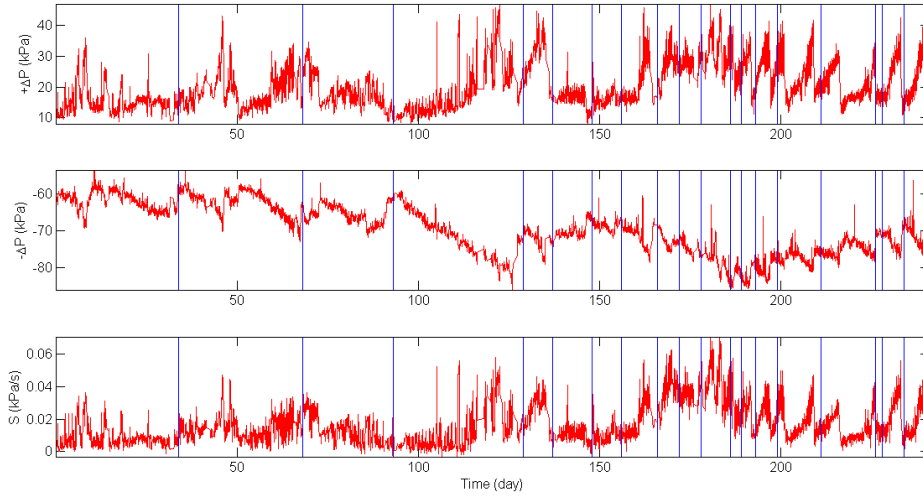


Figure 1.2: Smoothed values for the filtration pressure peak $+\Delta P$, the backwash pressure peak $-\Delta P$ and the slope S during 8 months of TMP sampling. Blue lines indicate Chemical Enhanced Backwash events.

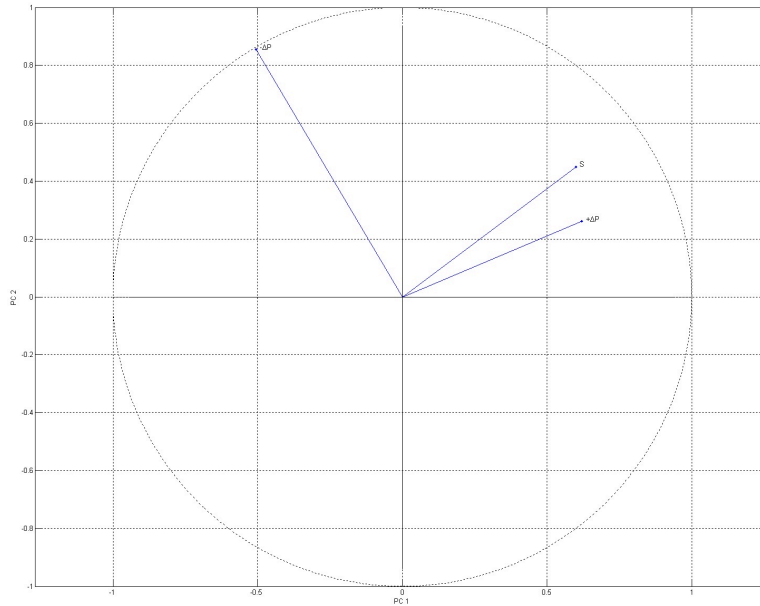


Figure 1.3: Biplot indicating the composition of PC1 vs. PC2.

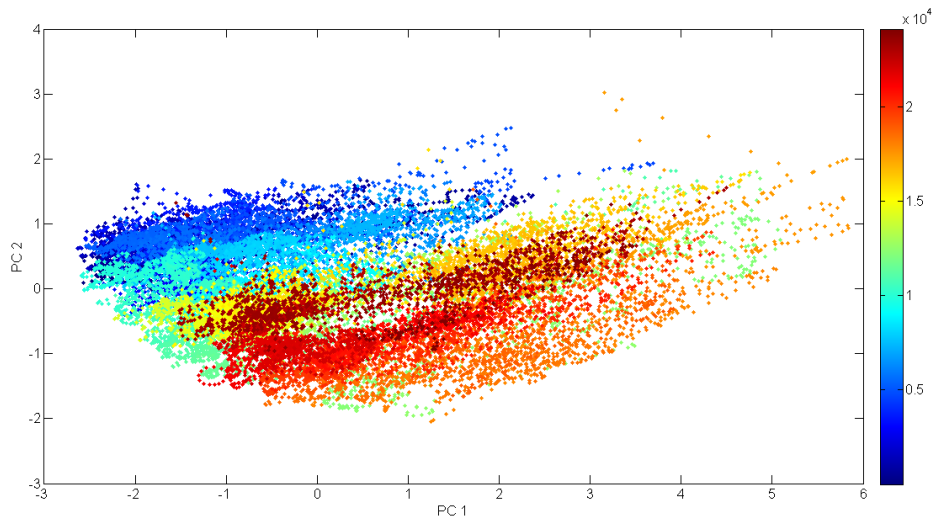


Figure 1.4: PCA score plot. Every dot represents one filtration cycle (n=24110). The color code from blue to red corresponds to the evolution of PC1 vs. PC2 between August 2011 (blue) and March 2012 (red)

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